medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Title: Mask mandates can limit COVID spread: Quantitative assessment of month-over-month effectiveness of governmental policies in reducing the number of new COVID-19 cases in 37 US States and the District of Columbia

Authors: Michael J. Maloney[1], Nathaniel J. Rhodes[2-4#], Paul R. Yarnold[5]

Affiliations: [1]Proof School, San Francisco, CA, USA; [2]Department of Pharmacy, Northwestern Memorial Hospital, Chicago, IL, USA; [3]Department of Pharmacy Practice, Midwestern University Chicago College of Pharmacy, Downers Grove, IL, USA; [4]Pharmacometrics Center of Excellence, Midwestern University Chicago College of Pharmacy, Downers Grove, IL, USA; [5]Optimal Data Analysis, LLC, Chicago, IL, USA

#Contact information corresponding author: Nathaniel J. Rhodes, PharmD, MSc, BCPS AQ-ID Midwestern University Chicago College of Pharmacy, Department of Pharmacy Practice. 555 31st Street Downers Grove, IL 60515, USA; Tel: 630-515-7376; Email: nrhode@midwestern.edu

Running title: Mask Mandates and New COVID-19 Cases

Funding Information: The author(s) received no specific funding for this work.

Competing Interests: The authors have declared that no competing interests exist.

Keywords: SARS-CoV-2; COVID-19; masks; public health; epidemiology, policy

Abstract *word* count: 250 **Manuscript *word* count:** 4191

NOTE: This preprint reports new research that has not been certified by peer review and should not be used to guide clinical practice.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

ABSTRACT

Introduction: SARS-CoV-2 is the beta-coronavirus responsible for COVID-19. Facemask use has been qualitatively associated with reduced COVID-19 cases, but no study has quantitatively assessed the impact of government mask mandates (*MM*) on new COVID-19 cases across multiple US States.

Data and Methods: We utilized a non-parametric machine-learning algorithm to test the *a priori* hypothesis that *MM* were associated with reductions in new COVID-19 cases. Publicly available data were used to analyze new COVID-19 cases from 37 States and the District of Columbia (i.e., "38 States"). We conducted confirmatory All-States and State-Wise analyses, validity analyses [e.g., leave-one-out (LOO) and bootstrap resampling], and covariate analyses.

Results: No statistically significant difference in the daily number of new COVID-19 infections was discernable in the All-States analysis. In State-Wise LOO validity analysis, 11 States exhibited reductions in new COVID-19 and the reductions in four of these States (AK, MA, MN, VA) were significant in bootstrap resampling. Only the Social Capital Index predicted *MM* success (training $p<0.028$ and LOO $p<0.013$).

Conclusion: Results obtained when studying the impact of *MM* on COVID-19 cases varies as a function of the heterogeneity of the sample being considered, providing clear evidence of Simpson's Paradox and thus of confounded findings. As such, studies of *MM* effectiveness should be conducted on disaggregated data. Since transmissions occur at the individual rather than at the collective level, additional work is needed to identify optimal social, psychological, environmental, and educational factors which will reduce the spread of SARS-CoV-2 and facilitate *MM* effectiveness across diverse settings.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

INTRODUCTION

The significance of respiratory droplets and airborne viral particles in the spread of SARS-CoV-2 and propagation of the COVID-19 pandemic gained early attention.[1] Asymptomatic carriage of SARS-CoV-2 is important to community spread because these individuals can transmit the virus in exhaled breath.[2, 3] Corollary research reported that face masks are protective[4-7] and may limit the severity of COVID-19 among individuals who become infected.[8] Indeed, the Centers for Disease Control and Prevention (CDCP) has advocated wearing a facemask when social isolation is impossible or impractical,[9] and recently reported that dining-out is among the riskiest known activities during the coronavirus pandemic—since face masks *are not used* when people are eating and drinking.[10] Other activities associated with an increased risk of SARS-CoV-2 transmission include singing[11] and aerosol generating procedures in the healthcare setting.[12] Small droplet formation, which can lead to aerosolization of the virus, is a major driver of infection risk,[13] thus wearing a facemask is expected to reduce inhalation of aerosolized virus.[4] Indeed, low rates of positive serology were observed (i.e., < 4% n=1/27) when healthcare workers followed aerosol minimizing procedures *and* used personal protective equipment to perform deep respiratory sampling in patients with COVID-19.[14] Thus, there is consensus in the scientific, clinical, and business communities that appropriate wearing of facemasks is a “best-practice” personal behavior, which can reduce the chances of being infected by, or of infecting others with, SARS-CoV-2 and other airborne disease-causing microbes.

Mathematical and time-series models of COVID-19 data collected in the US investigated salutary effects of masking on reducing the spread of the pandemic.[15, 16] These models suggest that a consistent application of best-practice public-health orders and citizen behaviors is needed to slow the spread of the pandemic.[17] A hybrid modeling approach used by the Institute for Health Metrics and Evaluation predicted that if 95% of people in the US wore masks outside their homes, the number of projected deaths from COVID-19 would drop by half within four months.[18] Thus, experts hypothesize that Mask Mandate

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

(*MM*) orders should result in reduced COVID-19 transmission and fatalities—assuming that the individuals in the community adhere to the *MM*.

Encouraged by research findings that wearing masks reduces the number of new COVID-19 cases, and motivated to intervene by increasing numbers of cases, Governors of 37 US States and the District of Columbia (hereafter called the "38 States") issued *MM* orders. However, the lack of clear, consistent Global, Federal, and State guidance on the use of face coverings (e.g., mandates *vs*. recommendations), and on who should be using masks (e.g., essential workers *vs*. private citizens), has initiated a nation-wide naturalistic experiment.[15] In the absence of clear guidance and direct leadership, variations in *MM* acceptance and enforcement have arisen within and between US States.[17, 19-22]

Promulgating and exacerbating confusion regarding the effectiveness of wearing face masks, adjudicating the effectiveness of *MM* orders has largely been left to *qualitative interpretations* and *visual/numerical inspections* of the epidemic curves depicting the number of new cases over time. Qualitative assessment cannot objectively test the *a priori* hypothesis that wearing a mask in public spaces reduces the incidence of COVID-19 cases. Accordingly, using publicly-available data, we employ non-parametric maximum-accuracy machine-learning to *quantitatively* test the confirmatory (*a priori*) hypothesis that imposing a *MM reduced* daily number of new COVID-19 cases in the month *after vs*. *before* the *MM*.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

METHODS

Hypotheses

First, merging data from all 38 States in which the Governor issued a *MM*, we test the *a priori* hypothesis that "*All-States*" imposition of a *MM reduced* the daily number of new COVID-19 cases in the month *after vs*. in the month *before* the *MM*. States were included if State leadership (e.g., Governors) had mandated the use of facemasks by all public-facing employees.

Second, considering each State individually, we test the *a priori* hypothesis that "*State-Wise"* imposition of *MM reduced* the daily number of new COVID-19 cases in the month *after vs*. in the month *before* the *MM*.

Data

The daily number of new COVID-19 cases was obtained separately for each State in the month *before* the *MM* was made (maximum of 30 days), and in the month *after* the *MM* was made (maximum of 31 days). Case reports occurring before the *MM* were dummy-coded as class=0, and case reports occurring after the *MM* were coded as class=1. Data from The New York Times, based on reports from State and local health agencies, were initially downloaded from GitHub on August 8, 2020 (data re-confirmed on September 23, 2020)[23] and cross referenced against the COVID-19 State Policy Database (data through June 1, 2020) for dates that *MM* were issued in each State.[24]

Our decision to compare daily number of new cases in the month before *vs*. the month after the *MM* was based on methodological and statistical considerations. First, *MM* orders were made because the day-over-day increases in the number of new cases threatened the ability of available health care resources to meet patient and healthcare worker needs. Therefore, the month following the *MM* naturally offers great opportunity for increased mask wearing to meaningfully reduce the number of new cases. Second, some amount of time is required after the *MM* is made for citizens (who wish to comply) to obtain masks, learn

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

how and when to wear them, and how to care for them, and for new infections occurring in the two-week period prior to the *MM* to develop symptoms after the *MM* was made. Third, to maximize the available statistical power of our analyses for estimating short-term effects (see *Statistical Analysis*), we extracted the number of cases for up to 30 days before and up to 31 days after the *MM* was implemented (yielding a maximum of n=61 data points for each state).

Additional attributes, obtained for individual States, were used in an attempt to discriminate States for which a *MM* did *vs*. did not reduce the number of new COVID-19 cases. Numerical attributes included population estimates,[26] gross domestic product (State and per capita),[27] age (with arbitrary brackets of 0-18, 18-25, 26-34, 35-54, 55-64, and 65+),[28] pre-pandemic (January 2020) number of unemployed persons and rate,[29] homelessness,[30] shelter beds,[31] incarceration number and rate,[32] number of nursing home residents,[33] population density (people per square mile in 2015),[34] urban overcrowding (number of houses having >1 person per room),[35] severe urban overcrowding (number of houses having >1.5 people per room),[35] ethnicity (white, black, and Hispanic categories),[36] Social Capital Index (a measure of social cohesion, where higher positive numbers indicate greater societal cohesion),[37] and obesity.[38] Categorical attributes included if the State's Governor wore a mask in public after the *MM* was made (0=Did not wear mask, 1=wore mask) which was assessed using media reports and public database image searches, the Governor's political party (0=Republican, 1=Democrat),[39] and the Governor's gender (0=Female, 1=Male).[40]

Statistical Analysis

We used confirmatory *O*ptimal *D*iscriminant (or *D*ata) *A*nalysis (ODA) to ascertain the *predictive accuracy* attained by using maximum-accuracy models to evaluate the *hypothesized reduction in the number of new cases* occurring subsequent to the *MM*.[41-43] ODA is the moniker of the statistically-motivated non-parametric machine-learning algorithm which identifies the cut-point for an ordered *attribute* (i.e., "independent variable"), or the assignment rule for a categorical attribute, which yields the

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

133 *strongest achievable accuracy* in discriminating between two or more class categories (i.e., "dependent
134 variable") for a given sample and hypothesis.[41-43] In the present study all hypotheses were confirmatory.[42]
135 For both the All-States (38-State) and the State-Wise analysis, the *a priori* hypothesis was that the *MM*
136 (up to 31 days) reduced the number of new cases.[44, 45]

137 An ODA model is obtained by iterating through every possible different assignment rule that is consistent
138 with the *a priori* hypothesis, and identifying the model achieving the highest effect strength for sensitivity
139 (ESS) statistic.[41, 42] An index of classification accuracy adjusted to remove the effect of chance, ESS is a
140 function of the mean sensitivity of the model achieved across class categories, standardized such that 0
141 represents the discriminatory accuracy which is expected by chance, 100 represents errorless (perfect)
142 discrimination, and values of $-100 \leq ESS < 0$ represent accuracy which is worse than expected by chance.
143 For a two-category *class variable* such as studied herein (i.e., month before *MM*=class 0 *vs*. month after
144 *MM*=class 1),

145 Mean Classification Accuracy (%) = 100 x [(sensitivity for class 0 + sensitivity for class 1)/2], (1)
146 and
147 ESS = 100 x [(Mean Classification Accuracy–50)/50]. (2)

148 A nonparametric permutation test which requires no distributional assumptions is used to assess the
149 statistical significance (*p* value) of the achieved ESS.[41, 44, 45] Point estimates of *p* values for tests of
150 statistical hypotheses reported herein are indicated as being statistically significant ($p \leq 0.05$) at either the
151 *experimentwise* (confirmatory $p \leq p_{Bonferroni}$) or the *per-comparison* (confirmatory $p \leq 0.05$) criterion.[42]

152 Internal model validation was conducted using bootstrap resampling[46, 47] (n=25,000) of the State-Wise
153 models within the *ODA* package for R.[48] Specifically, resampling with 50% replacement was conducted
154 using the LOO (i.e., validity) ODA model confusion matrix for each State. Exact discrete 95% confidence
155 intervals (CI) for the given ODA model ("Model") and for randomly scrambled observations from the

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

model ("Chance") were obtained.[46] Graphical depictions of new cases organized across days, and histograms of bootstrapped 95% CIs, were created using *ggplot2* for R.[49]

Potential generalizability of the ODA model applied to classify an independent random sample is assessed using a one-sample "leave-one-out" (LOO) jackknife analysis.[42] The sample size offers greater than 90% power to identify an ODA model of moderate strength (i.e., 25≤ESS<50).[50]

Exploratory ODA analyses were conducted to model the association of inter-State differences 28 variables (e.g., age, wealth, population density) conceivably capable of discriminating States which did *vs*. did not exhibit the predicted decline in number of new cases in the month following a *MM* (see *Data Supplement*).[42]

Sensitivity analyses were conducted comparing the initial data (obtained August 8, 2020) to the data obtained September 23, 2020. The percentage difference between the two datasets were calculated for each value [i.e., 100 x ($data_{new}$-$data_{old}$) / $data_{old}$] to quantify differences between datasets. In sensitivity analyses, any differences between datasets were compared according to the ODA model cut-points obtained using the initial data to determine whether the model was invariant to new (updated) data.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

RESULTS

All-States Analysis

The *mean* number of new COVID-19 cases before *vs*. after the *MM* for the sample of 38 States was 654 (N=1138, SD=1357) *vs*. 639 (N=1177, SD=975), respectively. In three instances, the daily report of new cases appeared to be outliers (GA 4/12/20, LA 5/29/20, and VA 5/6/20) and were coded as missing (i.e., coded as -999). Confirmatory ODA was used to test the *a priori* hypothesis that imposition of a *MM* reduced the *number* of new COVID-19 cases (the attribute) one-month *after vs*. one-month *before* the *MM* (the class variable). The confirmatory ODA model was: if >4 new cases-per-day then predict pre-*MM*; otherwise if ≤4 new cases-per-day, then predict post-*MM*. In training (using all observations from the sample) analysis, this model correctly classified 98.1% of the pre-*MM* cases, and 6.1% of the post-*MM* cases: ESS=4.1 (a weak effect), $p<0.13$.

Thus, when considering all 38 States having a *MM* as a single sample, there was no statistically significant difference in the daily number of new COVID-19 infections in the month before *vs*. the month after the *MM*.

State-Wise Analysis

As seen in Table 1, after the *MM* the *mean* number of new daily cases was numerically *lower* in 13 States (AK, GA, HI, LA, MA, MI, MN, NY, VA, VT, WA, WV, WY) post-*MM*, and numerically *higher* in the remaining 25 States. Table 2 gives the findings of ODA used to test the *a priori* hypothesis that State-Wise imposition of a *MM* (made by 38 different State Governors) *reduced the number of new COVID-19 cases* in the month *after vs*. in the month *before* the *MM*—with each State considered individually. In each State-Wise analysis, the class variable was a binary coded variable signifying the period before *vs*. after the *MM* occurred, and the attribute was the daily number of new cases. In Table 2, the States are ordered from strongest to weakest ESS of the confirmatory ODA model in training analysis.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Among all 38 States, training data for Minnesota (MN, the first State in Table 2) offer the greatest support for the *a priori* hypothesis. The ODA model is: if >480 new cases-per-day, then predict pre-*MM*; otherwise if ≤480 cases-per-day, then predict post-*MM*. This ODA model correctly classified 28 of 30 (93.3%) of the pre-*MM* days, and 27 of 31 (87.1%) of the post-*MM* days, thereby yielding a *strong*[42] ESS=80.4, $p<0.0001$. However, this model showed modest instability in LOO jackknife analysis (*relatively strong*[42] ESS=73.9, $p<0.0001$). In contrast, data for Alaska (AK, second row in Table 2) had the second-strongest training effect (*strong* ESS=80.3, $p<0.0001$), which was stable in LOO analysis. Among all 38 States, only AK returned a *strong* confirmation of the *a priori* hypothesis in training and LOO analysis.

Of the total of 38 States included in this study, 11 (23.7%) achieved confirmatory $p<0.05$ at the experimentwise criterion, and two (5.3%) achieved confirmatory $p<0.05$ at the per-comparison criterion[42] (Table 2). Three States (MN, AK, HI) yielded a training model indicating a *strong* confirmation[42] (i.e., ESS≥75) of the *a priori* hypothesis. Five States (MA, VT, VA, MI, NY) yielded a training model indicating a *relatively strong* confirmation[42] (i.e., 50≤ESS<75). And, three States (LA, WA, WY) yielded a training model indicating a *moderate* confirmation[42] (i.e., 25≤ESS<50) of the *a priori* hypothesis.

Except for GA and WY, States having a numerically greater *mean* number of new daily cases pre- *vs*. post-*MM* (Table 1) also had statistically-significant (at either the experimentwise or the per-comparison criterion[42]) confirmatory (Table 2) and LOO (Table 3) ODA models supporting the *a priori* hypothesis.

For all 11 States in Table 2 having training $p<0.05$, Table 3 presents 95% exact discrete CIs obtained for model and for chance.[46] For AK, VA, MA, and MN, the *lower bound* of the 95% exact discrete CI *for model* is greater than the *upper bound* of the 95% exact discrete CI *for chance*—therefore the result is statistically significant. For the remaining seven States, the upper bound for chance exceeded the lower bound for the model, so the result was not statistically significant in bootstrap validity analysis.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

For example, the daily number of new COVID-19 cases one-month pre- and one-month post-*MM* is illustrated in Figure 1.A for MN. Figure 1.B is a graphical summary of the model and chance bootstrap results: the blue histogram represents chance, the red histogram represents the model, the Y axis is frequency of the result in the Bootstrap analysis, and the X axis is training ESS. The dashed vertical lines inside the Figure represent the lower 95% CI for the model (red dashes), and the upper 95% CI for chance (blue dashes). When the blue dashes are on the same side as the blue histogram, and the red dashes are on the same side as the red histogram, the effect is statistically significant. Thus, evaluating MN in training analysis, the *a priori* hypothesis is accepted with experimentwise $p<0.05$.

In contrast, Figure 2.A presents the daily number of new COVID-19 cases one-month pre- and one-month post-*MM* for WA, and Figure 2.B is a graphical summary of the model and chance bootstrap results. Since the blue dashes are on the side of the red histogram, and the red dashes are on the side of the blue histogram, the hypothesized effect is not statistically significant for WA.

Modeling Success *vs*. Failure of a *MM* Order in Reducing the Number of New COVID-19 Cases

Finally, ODA was used to discriminate the four States (AK, MA, MN, VA) having a significantly lower number of new cases after the *MM vs*. the 34 States which did not support the *a priori* hypothesis. The only attribute which met the per-comparison criterion for statistical significance[42] was SCI, a measure of societal cohesion and the closeness of social ties.[51] The ODA model was: if SCI≤0.311, then predict the *MM did not reduce* the number of new cases of COVID-19; otherwise if SCI>0.311 then predict the *MM reduced* the number of new cases. In training ($p<0.028$) and LOO ($p<0.013$) analysis this model correctly classified all four States in which the *MM* reduced the number of new cases, and 25 of 35 (71.43%) States in which the *MM* failed to reduce the number of new cases. This level of classification accuracy corresponds to ESS=71.43, indicating a relatively strong effect.[42]

Sensitivity analyses

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

239 The dataset obtained on August 8, 2020 to was compared to a dataset obtained on September 23, 2020
240 and after exclusion of outliers (n=3), case numbers in the new dataset matched the original dataset (i.e.,
241 0% difference) for all states except Oregon (n=12/61) and Virginia (n=5/12), for which the new data fell
242 within ±6% of the original data. These numerical changes in data values (none of which were near the
243 ODA model cut-points) did not change the ODA model, the accuracy (ESS), or statistical significance (*p*)
244 of the model in training or LOO analysis for any model.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

DISCUSSION

An *All-States* analysis was conducted using merged data for 38 US States. Results indicated *no statistically significant decrease* in the number of new daily COVID-19 cases in the month before *vs*. after the *MM* was made. In contradistinction, a *State-Wise* analysis identified *clear evidence of State-specific MM effectiveness in reducing the number of new cases within one month of enactment* for multiple States (Tables 2 and 3). Such clear inconsistency is attributable to improper analysis of merged samples creating an analytic anomaly called *Simpson's Paradox*—which may identify spurious relationships, may fail to identify actual relationships, and/or may over- or under-weight the strength of effects—in every area of quantitative empirical science.[42, 47] *Paradoxical confounding* exists when the finding obtained by statistical analysis conducted for a combined sample is different than the finding obtained by the same analysis conducted separately for the constituent samples.[52] In the setting of a public health emergency, such as the current pandemic, accurate knowledge of the effectiveness of public health interventions is essential so that public health authorities can communicate this to the public.

Combining disparate groups is the primary operating procedure in government, scientific, and media discussions about the number of new and cumulative daily, monthly, and total number of COVID-19 cases and fatalities. Examples of such combined groups include global (the maximum-possible combined group), regional (e.g., the northern hemisphere), continental (e.g., Europe, Africa), and country (e.g., China, US, India, Brazil, France, UK, Israel) daily and cumulative case counts.[53] However, disparities in regional increases in numbers of new cases prompted some analysts to issue a warning against focusing on National trends.[54] Findings presented herein—that four of 38 (10.5%) States reliably demonstrated the hypothesized reduction in number of new cases in the month after the *MM* was made—similarly suggest a warning against focusing on State trends. Cognizance of the need to combine groups in a manner that prevents invalid statistical conclusions begs the question of how small must a "catchment area" be to count new cases so as to prohibit paradoxical confounding. Unfortunately, it has been shown that Simpson's Paradox can even occur for single-subject, "N-of-1" designs.[55] Thus, while accurate case

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

counts and definitions are important for tracking the epidemiology of the pandemic, such measures do not necessarily reflect the "reality on the ground" in any specific community, nor can they reliably discern the individual effectiveness of public health interventions.

The current methodology of conducting after-the-fact pandemic accounting for convenient and familiar (statistically unmotivated) groups is obviously inadequate when it is considered from a problem-solving perspective that focuses on getting (and staying) ahead of the pandemic curve. Others have argued, early in the pandemic, that rapid and comprehensive contact tracing will empower understanding of the situations and the processes underlying new COVID-19 infections.[56] As is the case in fighting a wildfire, progress is made by going to the active location each day, extinguishing blazes, and reducing available fuel, rather than by assessing the number of acres which burned the day before. However, contact tracing is most effective when community spread is low, so multifaceted interventions are needed to control the spread of the pandemic and presently wearing a mask is the most efficacious known means of slowing the pandemic.[5, 6, 8, 15, 16]

Temporal counts of the number of new cases are an imprecise measure—including the month-over-month methodology used presently—for multiple reasons. Even with perfect *MM* compliance, there is an up to 14-day lag time between infection and presentation of symptoms, and potentially an even longer lag between infection and presentation at a healthcare facility. After a *MM* order is made, there are logistical problems in getting masks to people, and there is a learning curve for users—where, when and how to wear and care for masks. *MM* compliance is imperfect, and enforcement is difficult. Indeed, individual *MM* compliance is expected to be heterogeneous based on experimental evidence from behavioral psychology. Individuals are susceptible to cognitive biases and often use heuristics to address complex problems when uncertainty is high. Examples of such biases and heuristics related to *MM* use include availability bias (e.g., knowing someone who is sick *vs.* not), anchoring bias (e.g., fixation on initial recommendations to avoid mask use to preserve PPE), and substitution heuristics (e.g., physical

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

discomfort with wearing a mask is substituted for mask efficacy).[57] The impact of these and other biases and heuristics on mask effectiveness is currently understudied.

Because transmissions occur at the level of the individual, rather than at a State or National level, governments should emphasize best-practice personal behaviors, adequate contact tracing, and minimization of high-risk exposures. Indeed, we posit that the efficacy of mask wearing is not at question as this depends only on the use of the mask. Instead, the effectiveness of *MM* can be eroded by multiple factors including asymptomatic carriage, willful ignorance of *MM* and lack of knowledge of how and when to wear masks. Moreover, our State-Wise analysis supports the *a priori* hypothesis that *MM* do indeed have a significant salutary effect on the spread of the pandemic, but more work is needed to define the social, psychological, environmental, and educational facilitators that maximize *MM* effectiveness.

Experimentally speaking, the best test of public health intervention effectiveness (e.g., *MM*)—using a methodology called an "A (before intervention), B (after intervention)" design—would involve simultaneous uniform application, enforcement, and education around the intervention, coupled with exacting real-time contact-tracing. A science-based, consistent approach to disease management could reduce public misunderstanding in this realm, and diminish mistrust of the other public health interventions (e.g., vaccines currently under development).[58] Our analysis is limited because we were not able to utilize a rigorous AB analytic framework to test our *a priori* hypotheses. Rather, we took advantage of the naturalistic experiment created by the heterogeneous response to the pandemic across States to highlight the paradoxical results obtained when applying an All-States followed by a State-Wise analytic approach. Our analysis was limited to testing our *a priori* hypothesis and it is worth considering the time-dependent impact of *MM*. Additional work is needed to evaluate the impact of *MM* on the growth of the pandemic. Our analysis is conservative in that we focused only on reductions in new cases and may underestimate the true impact of *MM*. Future studies should evaluate the impact of MM on new deaths. Large-scale serological studies may provide more insights into the spread of SARS-CoV-2 *MM* in States with vs. those without early *MM*.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Finally, we found that SCI, a measure of social closeness and ties,[51] was a relatively strong predictor of *MM* effectiveness. This finding is notable in that SCI could be a facilitating factor that makes mandated public health interventions more efficient. For example, populations with higher levels of social cohesion are inherently more likely to work together when faced with a common problem based on a shared sense of identity and social bonds. However, this finding has limitations. States with higher SCI should not be interpreted as being inherently better at reducing new SARS-CoV-2 cases, but rather we believe this finding also supports a new corollary hypothesis that States with lower SCI may require different and multifaceted interventions to address the pandemic.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

CONCLUSION

We identified paradoxical confounding whereby the effect of *MM* orders when analyzed using the pooled data from all 38 States available differed when compared to a State-Wise analysis. Overemphasis placed on National or State-level trends may obscure the true effectiveness of important public health interventions such as mask wearing, because transmission events are stochastic and occur at the level of individuals. Thus, greater emphasis on the impact of personal behaviors on *MM* effectiveness and thorough contact tracing are needed to combat the pandemic. While societal factors reflected by measures like the SCI may facilitate the efficiency of interventions like *MM* in select regions, more work is needed to define the optimal set of interventions that reduce SARS-CoV-2 transmission for socially diverse populations. Finally, optimal experimental designs, measurements, and analytic approaches are needed to provide the public with a clearer understanding of the evolution of the pandemic, and feedback on how current public health interventions are performing, in order to begin to restore broad-based trust in the scientific method.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity.
All rights reserved. No reuse allowed without permission.

ACKNOWLEDGEMENT

We would like to acknowledge Dr. Alan Maloney for his helpful edits and suggestions in reviewing the drafts of this manuscript.

FUNDING:

No funding was received. This study was completed as part of our normal work.

DISCLOSURES:

All authors: No relevant disclosures.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

REFERENCES

[1] **Zhang R, Li Y, Zhang AL, Wang Y and Molina MJ** (2020) Identifying airborne transmission as the dominant route for the spread of COVID-19. Proceedings of the National Academy of Sciences 117: 14857-14863. doi: 10.1073/pnas.2009637117

[2] **Bae SH, Shin H, Koo H-Y, Lee SW, Yang JM, et al.** (2020) Asymptomatic Transmission of SARS-CoV-2 on Evacuation Flight. Emerging Infectious Diseases 26. doi: 10.3201/eid2611.203353

[3] **Centers for Disease Control and Prevention (CDC)** (2020) How COVID-19 Spreads. Available at: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html Accessed on: September 21, 2020

[4] **Leung NHL, Chu DKW, Shiu EYC, Chan K-H, McDevitt JJ, et al.** (2020) Respiratory virus shedding in exhaled breath and efficacy of face masks. Nature Medicine 26: 676-680. doi: 10.1038/s41591-020-0843-2

[5] **Wang X, Ferro EG, Zhou G, Hashimoto D and Bhatt DL** (2020) Association Between Universal Masking in a Health Care System and SARS-CoV-2 Positivity Among Health Care Workers. Jama 324: 703. doi: 10.1001/jama.2020.12897

[6] **Clase CM, Fu EL, Joseph M, Beale RCL, Dolovich MB, et al.** (2020) Cloth Masks May Prevent Transmission of COVID-19: An Evidence-Based, Risk-Based Approach. Annals of Internal Medicine 173: 489-491. doi: 10.7326/m20-2567

[7] **Mitze T, Kosfeld R, Rode J and Wälde K** (2020) Face Masks Considerably Reduce Covid-19 Cases in Germany [pre-print]. medRxiv. doi: 10.1101/2020.06.21.20128181

[8] **Gandhi M, Beyrer C and Goosby E** (2020) Masks Do More Than Protect Others During COVID-19: Reducing the Inoculum of SARS-CoV-2 to Protect the Wearer. Journal of General Internal Medicine. doi: 10.1007/s11606-020-06067-8

[9] **Centers for Disease Control and Prevention (CDC)** (2020) Considerations for Wearing Masks: Help Slow the Spread of COVID-19. Available at: https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/cloth-face-cover-guidance.html Accessed on: August 7, 2020

[10] **Fisher KA, Tenforde MW, Feldstein LR, Lindsell CJ, Shapiro NI, et al.** (2020) Community and Close Contact Exposures Associated with COVID-19 Among Symptomatic Adults ≥18 Years in 11 Outpatient Health Care Facilities — United States, July 2020. MMWR Morbidity and Mortality Weekly Report 69: 1258-1264. doi: 10.15585/mmwr.mm6936a5

[11] **Hamner L, Dubbel P, Capron I, Ross A, Jordan A, et al.** (2020) High SARS-CoV-2 Attack Rate Following Exposure at a Choir Practice — Skagit County, Washington, March 2020. MMWR Morbidity and Mortality Weekly Report 69: 606-610. doi: 10.15585/mmwr.mm6919e6

[12] **Semple MG, Tran K, Cimon K, Severn M, Pessoa-Silva CL, et al.** (2012) Aerosol Generating Procedures and Risk of Transmission of Acute Respiratory Infections to Healthcare Workers: A Systematic Review. PLoS ONE 7: e35797. doi: 10.1371/journal.pone.0035797

[13] **Anfinrud P, Stadnytskyi V, Bax CE and Bax A** (2020) Visualizing Speech-Generated Oral Fluid Droplets with Laser Light Scattering. New England Journal of Medicine 382: 2061-2063. doi: 10.1056/NEJMc2007800

[14] **Gao CA, Bailey JI, Walter JM, Coleman JM, Malsin ES, et al.** (2020) Bronchoscopy on Intubated COVID-19 Patients is Associated with Low Infectious Risk to Operators at a High-Volume Center Using an Aerosol-minimizing Protocol [pre-print]. medRxiv. doi: 10.1101/2020.08.30.20177543

[15] **Lyu W and Wehby GL** (2020) Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US. Health Affairs 39: 1419-1425. doi: 10.1377/hlthaff.2020.00818

[16] **Eikenberry SE, Mancuso M, Iboi E, Phan T, Eikenberry K, et al.** (2020) To mask or not to mask: Modeling the potential for face mask use by the general public to curtail the COVID-19 pandemic. Infectious Disease Modelling 5: 293-308. doi: 10.1016/j.idm.2020.04.001

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

[17] **Althouse BM, Wallace B, Case B, Scarpino SV, Berdhal A, et al.** (2020) The unintended consequences of inconsistent pandemic control policies [pre-print]. medRxiv. doi: 10.1101/2020.08.21.20179473
[18] **Institute for Health Metrics and Evaluation** (2020) New IHME COVID-19 Forecasts See Nearly 300,000 Deaths by December 1, However, Consistent Mask-Wearing Could Save about 70,000 Lives. Available at: https://www.prnewswire.com/news-releases/new-ihme-covid-19-forecasts-see-nearly-300-000-deaths-by-december-1--however-consistent-mask-wearing-could-save-about-70-000-lives-301107858.html Published on: August 6, 2020
[19] **Tapp T** (2020) Donald Trump Asks Reporter To Take His Mask Off At News Conference After He Asks About Atlantic Article. Available at: https://deadline.com/2020/09/donald-trump-asks-reporter-to-take-his-mask-off-at-news-conference-atlantic-story-1234572311/ Published on: September 07, 2020
[20] **Niedzwiadek N and Atterbury A** (2020) Colleges crack down on student behavior as virus threatens more closures. Available at: https://www.politico.com/news/2020/08/30/college-students-coronavirus-closures-404567 Published on: August 30, 2020
[21] **Moreno JE** (2020) Sturgis Motorcycle Rally was 'superspreading event' that cost public health $12.2 billion: analysis. Available at: https://thehill.com/homenews/state-watch/515453-sturgis-motorcycle-rally-was-superspreading-event-that-cost-public Published on: September 8, 2020
[22] **Groves S and Kolpack D** (2020) Dakotas lead US in virus growth as both reject mask rules. Available at: https://www.yahoo.com/news/virus-rises-dakotas-freedom-argument-144101521.html Accessed on: 9/12/2020
[23] **The New York Times** (2020) Coronavirus (Covid-19) Data in the United States. Available at: https://github.com/nytimes/covid-19-data Accessed on: September 22, 2020
[24] **Raifman J, Nocka K, Jones D, Bor J, Lipson S, et al.** (2020) COVID-19 US state policy database. Available at: www.tinyurl.com/statepolicies Accessed on:
[25] **The Atlantic Monthly Group** (2020) COVID Tracking Project at the Atlantic. Available at: https://covidtracking.com/data/download Accessed on: September 23, 2020
[26] **United States Census Bureau Population Division** (2019) Annual Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2010 to July 1, 2019. 2010-2019 Population Estimates. Available at: https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html Accessed on: December 30, 2019
[27] **Bureau of Economic Activity** (2019) Gross Domestic Product by State, 4th Quarter and Annual 2019 (PDF). Available at: www.bea.gov Accessed on: April 7, 2020
[28] **Kaiser Family Foundation** (2018) Population Distribution by Age. Available at: https://www.kff.org/other/state-indicator/distribution-by-age/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D Accessed on: December 04, 2019
[29] **Bureau of Labor Statistics** (2020) STATE EMPLOYMENT AND UNEMPLOYMENT -- JANUARY 2020. Available at: https://www.bls.gov/news.release/archives/laus_03162020.htm Accessed on: August 29, 2020
[30] **Department of Housing and Urban Development** (2020) 2007 - 2019 PIT Counts by State (XLSX). Available at: https://www.hudexchange.info/resource/3031/pit-and-hic-data-since-2007/ Accessed on: January 2020
[31] **Department of Housing and Urban Development** (2020) 2007 - 2019 HIC Data by State (XLSX). Available at: https://www.hudexchange.info/resource/3031/pit-and-hic-data-since-2007/ Accessed on: January 2020
[32] **Kaeble D, Cowhig M and Bureau of Justice Statistics** (2016) Correctional Populations In The United States, 2016. Available at: https://www.bjs.gov/index.cfm?ty=pbdetail Accessed on: August 29, 2020
[33] **Kaiser Family Foundation** (2020) Total Number of Residents in Certified Nursing Facilities. Available at: https://www.kff.org/other/state-indicator/number-of-nursing-facility-residents/?currentTimeframe=0 Accessed on: August 29, 2020

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

[34] **United States Census Bureau** (2020) National Population Totals and Components of Change: 2010-2019. Available at: https://www.census.gov/content/census/en/data/tables/time-series/demo/popest/2010s-national-total.html#par_textimage_2011805803 Accessed on: September 23, 2020
[35] **Bennefield R and Bonnette R** (2003) Structural and Occupancy Characteristics of Housing: 2000. Census 2000 Brief. Available at: https://www.census.gov/prod/2003pubs/c2kbr-32.pdf Accessed on: January 8, 2019
[36] **Kaiser Family Foundation** (2020) Population Distribution by Race/Ethnicity. Available at: https://www.kff.org/other/state-indicator/distribution-by-raceethnicity/?currentTimeframe=0 Accessed on: August 29, 2020
[37] **US Congress Joint Economic Committee (JEC) Committee** (2018) The Geography of Social Capital in America. Available at: https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america Accessed on: August 29, 2020
[38] **Centers for Disease Control and Prevention (CDC)** (2018) CDC 2018 obesity map, Adult Obesity Prevalence Maps. Available at: https://www.cdc.gov/obesity/data/prevalence-maps.html Accessed on: August 29, 2020
[39] **270 to Win** (2020) 2020 Gubernatorial Elections Map. Available at: https://www.270towin.com/2020-governor-election/ Accessed on: September 05, 2020
[40] **Center for American Women in Politics (CAWP)** (2020) Women in Statewide Elective Executive Office 2020. Available at: https://cawp.rutgers.edu/women-statewide-elective-executive-office-2020 Accessed on: September 05, 2020
[41] **Yarnold PR and Soltysik RC** (1991) Theoretical distributions of optima for univariate discrimination of random data. Decision Sciences 22: 739-752. doi:
[42] **Yarnold PR and Soltysik RC** (2005) Optimal data analysis: Guidebook with software for Windows. Washington, D.C.: APA Books. doi:
[43] **Yarnold PR** (2017) What is optimal data analysis? Optimal Data Analysis 6: 26-42. doi:
[44] **Soltysik RC and Yarnold PR** (1994) Univariable Optimal Discriminant Analysis:One-Tailed Hypotheses. Educational and Psychological Measurement 54: 646-653. doi: 10.1177/0013164494054003007
[45] **Carmony L, Yarnold PR and Naeymi-Rad F** (1998) One-tailed Type I error rates for balanced two-category UniODA with a random ordered attribute. Annals of Operations Research 74: 223-238. doi:
[46] **Rhodes NJ and Yarnold PR** (2020) Generating Novometric Confidence Intervals in R: Bootstrap Analyses to Compare Model and Chance ESS. Optimal Data Analysis 9: 172-177. doi:
[47] **Yarnold PR and Soltysik RC** (2016) Maximizing Predictive Accuracy. ODA Books. doi: 10.13140/RG.2.1.1368.3286
[48] **Rhodes NJ** (2020) ODA: a package and R-interface for the MegaODA software suite. R package version 1.0.1.3. doi:
[49] **Wickham H** (2016) ggplot2: Elegant graphics for data analysis. New York: Springer-Verlag. doi:
[50] **Rhodes NJ** (2020) Statistical Power Analysis in ODA, CTA and Novometrics. Optimal Data Analysis 9: 21-25. doi:
[51] **Hendrix M** (2018) The Surprising Geography of Social Capital in America. Available at: https://medium.com/@michael_hendrix/the-surprising-geography-of-social-capital-in-america-c6cef6bae50b Published on: June 29, 2018
[52] **Yarnold PR** (2016) Characterizing and Circumventing Simpson's Paradox for Ordered Bivariate Data. Educational and Psychological Measurement 56: 430-442. doi: 10.1177/0013164496056003005
[53] **Anonymous** (2020) Covid-19: New fear grips Europe as cases top 30m worldwide. Available at: https://www.bbc.com/news/world-54199825 Published on: 9/18/2020
[54] **Scott D** (2020) These 4 Midwestern states are seeing worrying Covid-19 spikes. Available at: https://www.vox.com/2020/9/2/21418812/covid-19-coronavirus-us-cases-midwest-surge Published on: September 2, 2020
[55] **Yarnold PR** (2013) Ascertaining an individual patient's symptom dominance hierarchy: Analysis of raw longitudinal data induces Simpson's Paradox. Optimal Data Analysis 2: 159-171. doi:

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

[56] **Kretzschmar ME, Rozhnova G, Bootsma MCJ, van Boven M, van de Wijgert JHHM, et al.** (2020) Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study. The Lancet Public Health 5: e452-e459. doi: 10.1016/s2468-2667(20)30157-2

[57] **Tversky A and Kahneman D** (1974) Judgment under Uncertainty: Heuristics and Biases. Science 185: 1124-1131. doi: 10.1126/science.185.4157.1124

[58] **Holcombe M, Yan H and Waldrop T** (2020) 'Mix of science and politics' leading to people's uncertainty about Covid-19 vaccine, NIH director says. Available at: https://www.cnn.com/2020/09/16/health/us-coronavirus-wednesday/index.html Published on: September 17, 2020

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Table 1: State-Wise Descriptive Statistics for Number of New Cases Pre- *vs*. Post-Mask Mandate (*MM*)

	Before *MM* (n≤30)		After *MM* (n≤31)	
State	Mean	SD	Mean	SD
AK	9.8	4.8	2.4	2.0
AL	229.4	64.1	390.3	158.0
AR	93.7	75.4	205.0	114.8
AZ	245.6	88.2	547.7	355.1
CA	1417.9	390.6	2147.9	464.8
CO	338.6	81.2	421.1	148.5
DC	68.0	52.3	155.3	52.7
DE	147.2	100.1	153.7	69.2
FL	754.3	263.8	863.7	305.2
GA	704.1	315.6	653.4	218.1
HI	17.1	9.4	3.4	4.3
IL	1564.2	504.7	2182.9	668.9
IN	530.7	134.4	559.0	132.2
KY	159.5	87.9	178.8	85.7
LA	760.2	606.1	399.2	237.0
MA	1925.7	718.4	1041.5	660.5
MD	385.2	292.1	911.0	240.9
ME	26.4	12.6	39.7	16.7
MI	1147.5	344.6	572.2	255.6
MN	637.7	116.4	383.6	101.5
MS	222.9	68.5	277.7	81.8
NE	179.6	152.3	296.1	109.6
NH	59.3	17.4	80.8	29.6
NJ	1480.3	1528.0	2936.7	808.8
NM	117.1	47.0	146.3	51.3
NV	120.8	38.8	124.9	42.7
NY	7479.5	2836.8	4170.2	2206.4
OH	503.5	288.7	574.1	106.9
OR	61.0	14.9	59.9	29.0
PA	1051.8	605.8	1150.4	355.1
RI	138.1	120.7	278.0	87.1
TX	923.8	222.6	1266.6	380.9
UT	65.9	56.0	137.8	34.7
VA	933.2	243.9	656.0	230.7
VT	25.1	16.2	5.5	5.2
WA	299.2	132.8	252.7	108.5
WV	31.8	17.7	28.4	19.5
WY	14.6	12.9	11.1	6.6

Legend: SD=Standard Deviation

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Table 2: Maximum-Accuracy Confirmatory Models Assessing State-Wise Mask Mandate (*MM*) Effectiveness

					Training		LOO[d]	
State	Pre-*MM*	Sensitivity (%)[a]	Post-*MM*	Specificity (%)[b]	*p*≤	ESS (%)[c]	*p*≤	ESS (%)[c]
MN	>480 Cases	28/30 (93.3)	≤480 Cases	27/31 (87.1)	0.0001	80.4	0.0001	73.9
AK	>4 Cases	27/30 (90.0)	≤4 Cases	28/31 (90.3)	0.0001	80.3	0.0001	80.3
HI	>6 Cases	26/30 (86.7)	≤6 Cases	28/31 (90.3)	0.0001	77.0	0.0001	64.0
MA	>1174 Cases	29/30 (96.7)	≤1174 Cases	23/31 (74.2)	0.0001	70.9	0.0001	64.3
VT	>14 Cases	23/30 (76.7)	≤14 Cases	29/31 (93.6)	0.0001	70.2	0.0001	66.8
VA	>691 Cases	27/29 (93.1)	≤691 Cases	23/31 (74.2)	0.0001	67.3	0.0001	67.3
MI	>732 Cases	26/30 (86.7)	≤732 Cases	24/31 (77.4)	0.0001	64.1	0.0001	50.8
NY	>4762 Cases	26/30 (86.7)	≤4762 Cases	22/31 (71.0)	0.0001	57.6	0.0001	51.0
LA	>340 Cases	26/30 (86.7)	≤340 Cases	17/30 (56.7)	0.0027	43.3	0.0037	36.7
WA	>294 Cases	17/30 (56.7)	≤294 Cases	25/31 (80.6)	0.011	37.3	0.0028	37.3
WY	>15 Cases	13/30 (43.3)	≤15 Cases	27/31 (87.1)	0.036	30.4	0.04	24.0
PA	>1389 Cases	12/30 (40.0)	≤1389 Cases	26/31 (83.4)	0.16	23.9	0.07	20.5
OR	>41 Cases	28/30 (93.3)	≤41 Cases	8/31 (25.8)	0.25	19.1	0.23	9.5
GA	>886 Cases	8/29 (27.6)	≤886 Cases	28/31 (90.3)	0.34	17.9	0.21	11.0
WV	>36 Cases	11/30 (36.7)	≤36 Cases	25/31 (80.6)	0.31	17.3	0.18	14.0
DE	>203 Cases	6/30 (20.0)	≤203 Cases	28/31 (90.3)	0.65	10.3	0.34	7.0
OH	>768 Cases	4/30 (13.3)	≤768 Cases	30/31 (96.8)	0.68	10.1	0.30	6.8
KY	>64 Cases	28/30 (93.3)	≤64 Cases	5/31 (16.1)	0.7	9.5	0.30	9.5
IN	>396 Cases	27/30 (90.0)	≤396 Cases	6/31 (19.4)	0.72	9.4	0.38	6.1
NV	>189 Cases	3/30 (10.0)	≤189 Cases	30/31 (96.8)	0.81	6.8	0.99	-77.1
NE	>455 Cases	3/30 (10.0)	≤455 Cases	30/31 (96.8)	0.81	6.8	0.82	-3.0
AL	>107 Cases	30/30 (100)	≤107 Cases	2/31 (6.4)	0.84	6.4	0.52	3.1
NJ	>4296 Cases	1/30 (3.33)	≤4296 Cases	31/31 (100)	0.94	3.3	0.88	-3.1
TX	>477 Cases	30/30 (100.0)	≤477 Cases	1/31 (3.2)	0.96	3.2	0.51	3.2
FL	>534 Cases	25/30 (83.3)	≤534 Cases	6/31 (19.4)	0.97	2.7	0.77	-3.9
NM	>216 Cases	2/30 (6.7)	≤216 Cases	29/31 (93.6)	0.98	0.2	0.94	-6.3
MS	>138 Cases	28/30 (93.3)	≤138 Cases	2/31 (6.4)	0.99	-0.2	0.95	-6.8
UT	>176 Cases	2/30 (6.7)	≤176 Cases	28/31 (90.3)	0.99	-3.0	0.99	-12.8
DC	>224 Cases	1/30 (3.3)	≤224 Cases	29/31 (93.6)	0.99	-3.1	0.88	-3.1
MD	>1154 Cases	1/30 (3.3)	≤1154 Cases	29/31 (93.6)	0.99	-3.1	0.94	-6.3
CO	>210 Cases	28/30 (93.3)	≤210 Cases	1/31 (3.2)	0.99	-3.4	0.89	-3.4
NH	>34 Cases	28/30 (93.3)	≤34 Cases	1/31 (3.23)	0.99	-3.4	0.95	-6.8
ME	>61 Cases	1/30 (3.3)	≤61 Cases	27/31 (87.1)	0.99	-9.6	0.99	-93.4
IL	>1133 Cases	26/30 (86.7)	≤1133 Cases	1/31 (3.2)	0.99	-10.1	0.98	-10.1
AR	>34 Cases	24/30 (80.0)	≤34 Cases	1/31 (3.2)	0.99	-16.8	0.99	-20.1
AZ	>161 Cases	24/30 (80.0)	≤161 Cases	1/31 (3.2)	0.99	-16.8	0.99	-20.1
RI	>273 Cases	9/30 (30.0)	≤273 Cases	16/31 (51.6)	0.99	-18.4	0.99	-41.7
CA	>2315 Cases	2/30 (6.7)	≤2315 Cases	21/31 (67.7)	0.99	-25.6	0.99	-32.2

Footnotes: a) Sensitivity gives the results for the predicted (numerator) and the actual (denominator) number of new cases after *MM*. b) Specificity gives the results for predicted (numerator) and actual (denominator) number of new cases before *MM*. c) ODA models explicitly maximize classification (i.e., predictive) accuracy adjusted for chance, which is assessed

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

by the effect strength for sensitivity (ESS) statistic: ESS=0 is the accuracy expected by chance; ESS<25 is a relatively weak effect; ESS<50 is a moderate effect; ESS<75 is a relatively strong effect; ESS<90 is a strong effect; and -100≤ESS<0 is accuracy which is worse than expected by chance. In this column, MN has a training model with an ESS that provides the strongest support for the *a priori* hypothesis and is statistically significant whereas CA has a training model that provides the least support for this hypothesis and is not significant. d) Classification performance in validity analysis was computed using a one-sample leave-one-out (LOO) jackknife validity assessment. In this column, AK has a validity model with an ESS that provides the strongest support for the *a priori* hypothesis and is statistically significant whereas ME has a validity model that provides the least support for this hypothesis and is not significant.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

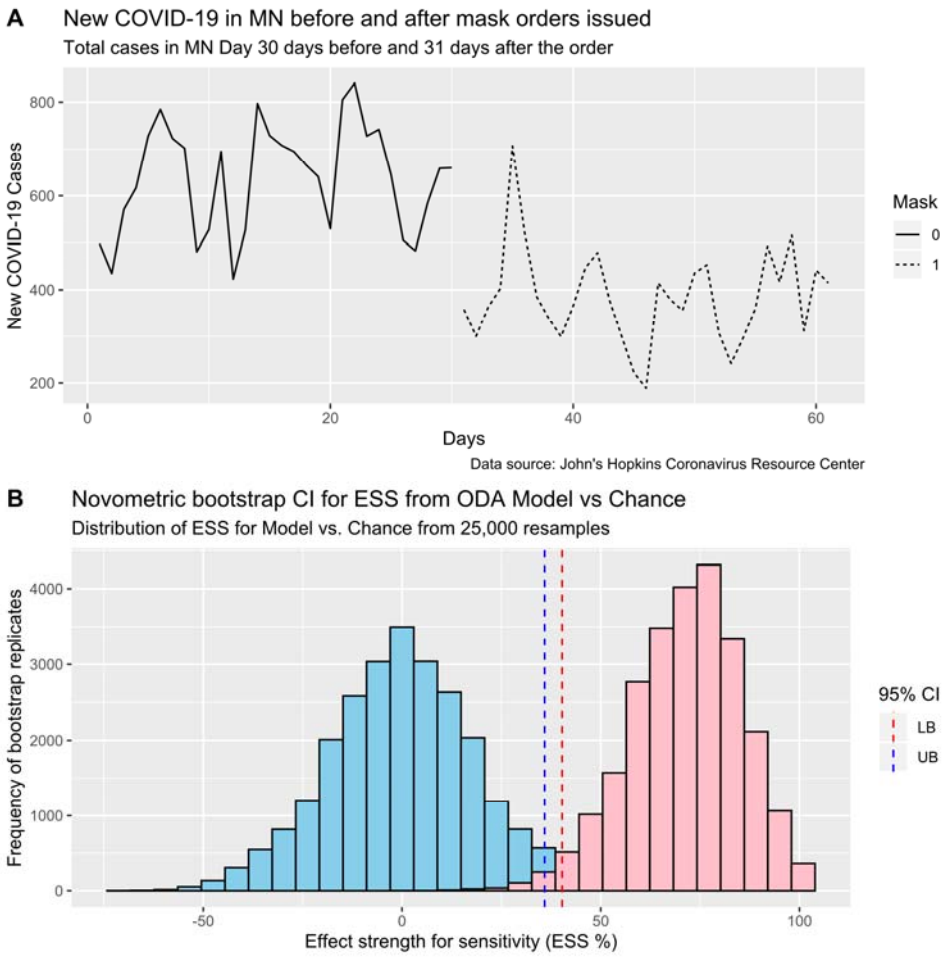
Table 3: LOO Confirmatory *p*, and Bootstrap 95% CI for LOO ESS, for 11 States Demonstrating Mask Mandate (*MM*) Effectiveness vis-à-vis Training $p<0.05$

State	$p <$	Chance 95% CI[a]	Model 95% CI[a]	95% CI overlap[b]
AK	0.0001	-36.1 – 35.9	64.6 – 100	No
VA	0.0001	-35.8 – 35.9	49.9 – 100	No
MA	0.0001	-35.0 – 34.8	41.7 – 92.9	No
MN	0.0001	-35.9 – 36.1	40.3 – 95.2	No
HI	0.0001	-36.1 – 35.9	34.9 – 91.7	Yes
VT	0.0001	-35.7 – 34.9	30.3 – 86.7	Yes
NY	0.0001	-36.1 – 35.8	25.5 – 86.1	Yes
LA	0.0037	-34.8 – 35.7	25.0 – 84.6	Yes
MI	0.0001	-35.8 – 36.1	11.1 – 76.6	Yes
WA	0.0028	-34.4 – 35.0	0.00 – 68.4	Yes
WY	0.04	-33.3 – 33.5	-10.1 – 58.3	Yes

Footnotes: a) Exact Discrete 95% Confidence Intervals (CIs) for Model and Chance ESS were estimated using bootstrap resampling of the ODA model confusion matrix from each respective State obtained in LOO analysis. b) For a given State, if the upper bound (UB) of the CI for chance falls *beneath* the lower bound (LB) of the CI for the model, this column indicates NO 95% CI overlap—so the confirmatory hypothesis is *accepted* (i.e., the *MM* reduced the number of new cases). And, for a given State, if the UB of the CI for chance falls *above* the LB of the CI for the model, this column indicates YES 95% CI overlap—so the confirmatory hypothesis is *rejected* (i.e., the *MM* did not reduce the number of new cases). In other words, if the exact discrete CIs for model and chance do not overlap, then the ODA model identified in LOO analysis is considered statistically robust and the findings are likely to be generalizable.

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Figure 1. Representative state (MN) with a strong impact of Mask Mandate (*MM*) orders



Legend:

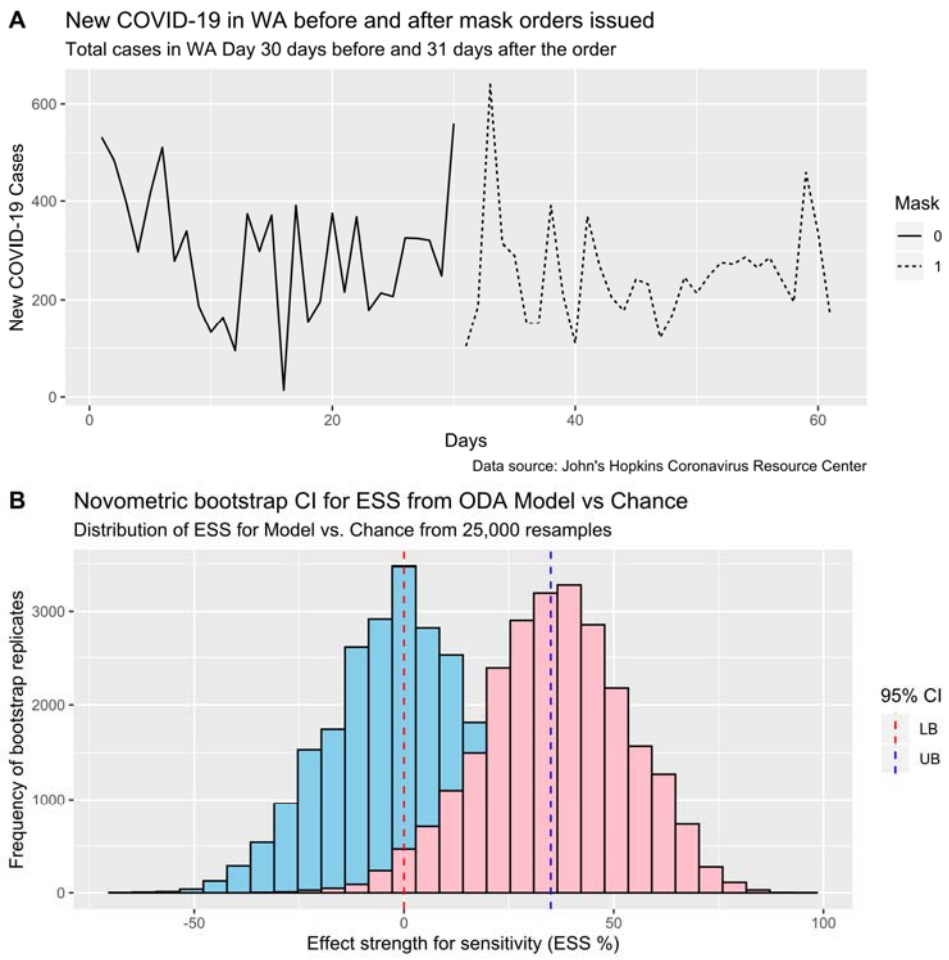
Panel A. Number of new COVID-19 cases reported within MN daily in the month before (solid black line) *vs.* daily in the month after (broken black line) *MM* orders were issued.

Panel B. Distribution of bootstrap replicates for model and chance for the LOO analysis for MN by ODA. Here, the ODA model was resampled using bootstrap resampling with replacement (n=25,000 resamples with 50% replacement) for the LOO model confusion matrix (see Table 3) as well as for chance (i.e., the final model predictions randomly scrambled relative to the class variable). The lack of overlap between the Chance UB and Model LB is denoted by the alignment (rather than reversal) of the dashed lines with the corresponding Chance (blue) and Model (red) bootstrap distributions.

Abbreviations: LB = lower bound of the 95% CI (i.e., 2.5th percentile); UB = upper bound of the 95% CI (i.e., 97.5th percentile); LOO = leave-one-out one-sample jackknife.[42]

medRxiv preprint doi: https://doi.org/10.1101/2020.10.06.20208033; this version posted October 8, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. All rights reserved. No reuse allowed without permission.

Figure 2. Representative state (WA) with a moderate impact of Mask Mandate (*MM*) orders



Legend:

Panel A. Number of new COVID-19 cases reported within WA daily in the month before (solid black line) *vs*. daily in the month after (broken black line) *MM* orders were issued.

Panel B. Distribution of bootstrap replicates for model and chance for the LOO analysis for WA by ODA. Here, the ODA model was resampled using bootstrap resampling with replacement (n=25,000 resamples with 50% replacement) for the LOO model confusion matrix (see Table 3) as well as for chance (i.e., the final model predictions randomly scrambled relative to the class variable). The overlap between the Chance UB and Model LB is denoted by the reversal (rather than alignment) of the dashed lines with the corresponding Chance (blue) and Model (red) bootstrap distributions.

Abbreviations: LB = lower bound of the 95% CI (i.e., 2.5th percentile); UB = upper bound of the 95% CI (i.e., 97.5th percentile); LOO = leave-one-out one-sample jackknife.[42]